PC-MRI derived inlet boundary conditions in CFD models of human aorta: uncertainty propagation

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PC-MRI DERIVED INLET BOUNDARY CONDITIONS IN CFD MODELS OF HUMAN AORTA: UNCERTAINTY PROPAGATION

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INTRODUCTION

In last decades, computational fluid dynamics (CFD) has been extensively applied to study vascular flows, proving to be an effective tool to gain insights into the intricate relationship between hemodynamics and vascular disease. More recently, coupling computational hemodynamics with cardiovascular imaging has allowed to build up even more realistic and personalized CFD models. In general, the reliability of patient-specific CFD results strongly depends on the level of uncertainty introduced in the modeling process, as many sources of uncertainty affect the accuracy of the image-based CFD results. To successfully translate CFD predictions into clinics, all the relevant uncertainty sources should be identified and propagated through the model equations to assess the level of uncertainty of the output variables of interest. This would allow to provide clinicians with model predictions together with the associated uncertainties, thus improving the added value of CFD tools in clinical practice. A number of studies have investigated the sources of uncertainty in computational hemodynamics models: reconstructed vessel geometry [1], boundary conditions (BCs) [2, 3], vessel distensibility and motion [4] and rheological properties of blood [5]. In a recent study, different possible strategies of applying PC-MRI measured flow data as BCs in computational hemodynamic models of human aorta were implemented [2]. The reported findings highlighted that the assumption of idealized velocity profiles as inlet BCs in personalized computational models can lead to misleading representations of the aortic hemodynamics. In this study, we investigate how uncertainty affecting PC-MRI measurements of blood velocity profiles, applied as inflow BCs to a personalized model of human aorta, propagates from the inlet section at the ascending aorta through the aortic territory and results in specific uncertainty of blood flow predictions. By means of Monte Carlo, CFD-based simulations, we provide advice on where, when and how it is important to account for inlet BCs uncertainty affecting PC-MRI measured velocity profiles.

METHODS

PC-MRI was used to obtain the anatomic model of a healthy human thoracic aorta (Fig. 1). Details on in vivo acquisitions and on model reconstruction can be found elsewhere [2]. PC-MRI phase flow measured data were used to prescribe blood flow velocity profiles at the ascending aorta (AAo) inflow section. The finite volume method was applied to solve the fluid motion equations in steady-state conditions. Steady flow analysis was adopted here to limit the overall computational cost of the Monte Carlo procedure. Different flow regimes, corresponding to three different phases of the cardiac cycle were considered: beginning of the systole (T1), peak systole (T2) and halfway of the systolic deceleration phase (T3). The flow regimes were characterized by a Reynolds number, at the AAo section, equal to 608, 5138 and 2497, respectively. Governing equations of motion were solved without turbulence closure, using second-order accuracy. The simulations were performed on a 5 million mesh for flow regimes T1 and T3 and on a finer 18 million mesh for T2. PC-MRI velocity measurements were used to obtain the 3D inlet boundary conditions in terms of velocity profiles at the AAo [2]. An explanatory example of measured velocity profile at the AAo is presented in Fig. 1d. The Monte Carlo method was used to propagate the uncertainty in measured PC-MRI velocity profiles applied as inflow BCs through the CFD model. This technique requires random generation of a large ensemble of inputs from their probability distributions and successive deterministic model simulations to generate many realizations of the output. In this work, at each cell centroid of the AAo inlet section, each PC-MRI velocity component was assumed to have Gaussian

distribution, where the mean is equal to the measured PC-MRI value and the standard deviation SD was set by assuming a signal to noise ratio (SNR) of the PC-MRI data equal to 16 [6], corresponding to a coefficient of variation equal to 6.25%. The SD value would imply a maximum deviation of inlet BC velocity data from the mean value of ±18%, when truncating the Gaussian distribution at ±3 SD. Here, the number of Monte Carlo runs was set equal to 100, i.e., the minimum value ensuring the convergence of the probability density functions of the output variables. Hence, for each simulated flow regime and each inlet BC scenario, 100 CFD experiments were performed for a total of 300 numerical simulations. Monte Carlo simulations were used to estimate the empirical probability density functions of hemodynamic quantities of interest at relevant anatomical landmarks. Namely, the uncertainty in the prediction of vessel cross-section averaged flow quantities was estimated at seven aortic cross-sections (Fig. 1). For each cross-section, mean and standard deviation of the empirical cumulative distribution function (ECDFs) of pressure, velocity and vorticity magnitude were estimated in order to estimate the SNR. Wall shear stress (WSS) uncertainty propagation at the luminal surface was also evaluated.

RESULTS

Fig.1 shows the SNR as estimated from the ECDFs of pressure, velocity and vorticity magnitude, at different flow regimes. In general, uncertainty in pressure is the highest and all locations show similar values of SNR. Table 1 reports the SNR of flow variables, averaged over the seven cross-sections selected for the analysis, for flow regimes T1, T2 and T3.

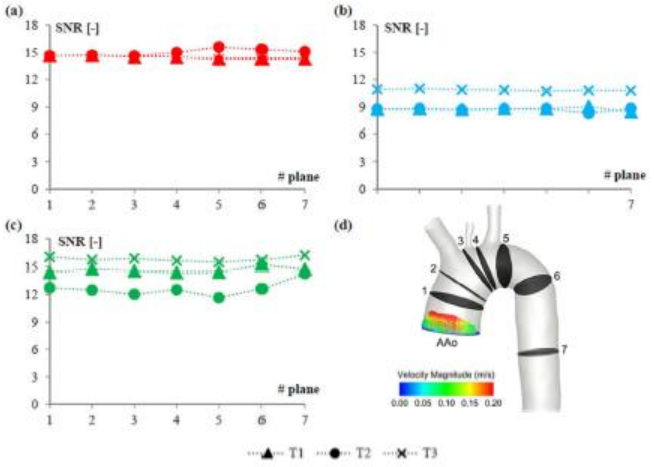

Figure 1: SNR of cross-section averaged blood velocity magnitude (a), pressure (b) and vorticity magnitude (c) at different positions along the aorta (d), at flow regimes T1,T2 and T3.

Data in Table 1 indicate that the predicted uncertainty is always higher than the prescribed input uncertainty (SNR lower than the prescribed SNR=16), with the exception of vorticity magnitude at T3. Noteworthy, blood pressure SNR can be up to 40% lower than SNR source at the inflow section. Regarding uncertainty variability with respect to the flow regime, no common trends can be identified for the three flow variables. In detail, velocity magnitude SNR is almost insensitive to flow regime, while the SNR of vorticity magnitude exhibits the highest variability, with flow regime T2 (peak systole) being the most affected by uncertainty. Finally, pressure uncertainty is higher at flow regimes T1 and T2, characterized by the same SNR, than T3. An additional analysis was performed to investigate the effect of the uncertainty in inlet BCs on WSS magnitude distribution. It was observed that uncertainty affecting WSS markedly differs between flow regime T2 (peak systole), and T1, T3. The value of the coefficient of variation averaged over the whole luminal surface is about 10% at flow regimes T1 and T3, and about 30% at T2. Marked differences were also be observed in the spatial distribution of WSS uncertainty (not shown). In all the cases investigated here, the uncertainty propagation in WSS calculation resulted to be higher than input uncertainty.

Flow regime	mean SNR velocity magnitude	mean SNR pressure	mean SNR vorticity magnitude
T1	14.4	8.8	14.6
T2	15.0	8.7	12.6
T3	14.4	10.9	15.8

Table 1. SNR of the considered flow quantities averaged over the seven cross section in Fig. 1, at flow regimes T1, T2 and T3.

DISCUSSION

This study aimed at investigating the impact of uncertainty in PC-MRI measurements of velocity profiles on patient-specific CFD modeling of aortic hemodynamics. The main findings of the study are that: (1) propagating the inflow BC uncertainty through the Navier-Stokes equations leads to a decrease in the SNR of CFD predictions with respect to the uncertainty source. This result holds for both intravascular flow quantities and WSS distribution, with higher uncertainties for the latter; (2) uncertainty affecting intravascular flow quantities does not present a marked dependence on anatomical location and flow regime. Differently, WSS uncertainty at peak systole is much higher than WSS uncertainty at decelerating/accelerating phases of the systole. One major limit of this work is the steady flow assumption. However, it should be noticed that: in Navier-Stokes equations, uncertainty is mainly propagated by the acceleration operator, where the non-linear advection contribution is expected to be predominant, compared to the local linear term; the computational cost of an unsteady simulation is about two orders of magnitude higher than a steady simulation, hence Monte Carlo unsteady experiments are not affordable unless resorting to HPC platforms. For these reasons, the approach proposed here does make scientific sense and paves the way to further investigations, adopting more efficient stochastic methods to propagate input uncertainty in a more realistic, time-dependent simulation scenario. The approach here adopted emphasizes that PC-MRI flow measurements-derived uncertainty is an important source of uncertainty. This is of utmost importance considering that it is non-linearly related with other uncertainties intrinsic in modeling assumptions. As a consequence, the global effect could not be neglected when looking at model reliability.

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